The Use of Smoothed Earnings Information by Analysts

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Abstract

This study examines (1) whether analysts' forecasts fully incorporate smoothed earnings information, and (2) whether firms that smooth earnings are associated with more favorable stock recommendations. Two aspects of information contained in smoothed earnings are examined: income smoothing and reported earnings variability. Our results demonstrate that analysts' forecasts fully incorporate the information contained in income smoothing, when the resulting reported earnings series is not volatile. When reported earnings show high variability, an increase in income smoothing is associated with more optimistic analysts' forecasts (resulting in negative forecast errors), and less favorable recommendations.

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1 Introduction

The practice of manipulating accounting accruals in order to reduce fluctuations in a time series of reported earnings is termed "income smoothing" (Ronen and Sadan 1981). Managers employ smooth reported earnings patterns to signal earnings prospects to shareholders, because direct disclosures of private information are costly or impractical (Schipper 1989; Demski 1998; Demski and Sappington 1987). If smooth earnings signals convey information about firm prospects, we expect that sophisticated users of financial reports (such as equity analysts) will incorporate the information contained in these signals in their earnings forecasts and stock recommendations. In this study, we extend prior research on income smoothing by investigating (1) whether analysts' forecasts fully incorporate the information contained in smoothed earnings, and (2) whether firms that smooth earnings are associated with more favorable stock recommendations.

In order to successfully communicate a firm's earnings prospects through income smoothing, the resulting reported earnings series must show a smooth trend (Demski 1998; Chaney and Lewis 1995). When managers lack information about future earnings, attempts to smooth earnings can create more variability in earnings (Tan and Jamal 2006; Sunder 1997). In addition, managers can smooth earnings in order to satisfy objectives other than the communication of firm prospects. For instance, managers can use accruals to smooth earnings in order to satisfy bonus plan criteria (Healy 1985), extend employment tenure (Fudenberg and Tirole 1995), and meet analysts' expectations (Kasznik and McNichols 2002). Consequently, observations of high income smoothing in firms need not necessarily imply that the reported earnings pattern is

smooth. Similarly, the absence of smoothing does not imply that the reported earnings series is volatile. The firm could have a stable underlying economic earnings series such that smoothing with accruals is not required.

The issues discussed here suggest that income smoothing (i.e. the use of accruals to manage earnings) and smoothness of reported earnings (i.e. lack of variability in reported earnings) are distinct, and that there is an interaction between these two variables. Prior evidence shows that income smoothing by managers reveals information about future earnings prospects (Tucker and Zarowin 2006), and that analysts do not fully incorporate information about the variability of reported earnings into their earnings forecasts (Dichev and Tang 2009). There is however, no evidence on whether income smoothing by managers enables analysts to generate more accurate forecasts. Neither is there evidence on whether the information contained in smoothed earnings series conveys sufficiently credible prospects of future earnings, which will be translated into favorable stock recommendations. Prior research on stock recommendations indicates that analysts who issue more accurate forecasts also issue more profitable stock recommendations (Loh and Mian 2006; Ertimur, Sunder and Sunder 2007). However, the use of smoothed earnings information for stock recommendations has not been investigated.

Our first objective is to examine whether analysts' forecasts fully incorporate the information contained in smoothed earnings. Analysts' forecasts of earnings are widely used as a proxy for market expectations of earnings in the derivation of asset valuation (Fried and Givoly 1982; O'Brien 1988). The accuracy of analysts' forecasts is important for the efficient functioning of capital markets (Abarbanell and Bernard 1992). Consequently, analysts' forecasts are useful to the extent that they incorporate information that has an impact on future earnings. There is a large literature that examines whether analysts fully utilize information that can impact future

earnings in their formulation of earnings forecasts (see reviews by Ramnath, Rock and Shane 2008; Brown 1993). A recent study by Tucker and Zarowin (2006) shows that income smoothing by managers reveals information about earnings prospects. They find that past earnings have a greater explanatory power for future earnings when managers smooth earnings. Consequently, we expect that analysts would use the information related to income smoothing in their formulation of earnings forecasts. Our study is related to Dichev and Tang (2009) who find that analysts do not fully incorporate the information about the variability of reported earnings in their forecast of future earnings. However, Dichev and Tang do not examine the information contained in income smoothing by managers. Thus, we extend the work of Dichev and Tang (2009) by examining the effects of income smoothing, smoothness of earnings and their interaction, on analysts' forecast errors.

The second objective of this study is to investigate whether firms that smooth earnings are associated with more favorable recommendations. Theoretical researchers posit that managers use smoothed earnings to communicate future firm prospects (Demski 1998; Chaney and Lewis 1995). Smoothed earnings information affects forecasts by reducing the uncertainty associated with future earnings, which enables analysts to provide more accurate forecasts. Further, because smoothed earnings also communicates firm prospects, smooth earnings are expected to additionally influence an analyst's stock recommendation. Previtts et al. (1994) find that analysts have a preference for smoothed reported earnings. Consequently, if analysts use the information contained in smooth earnings in their evaluation of a firm's future prospects, we expect that successful income smoothing by managers will be significantly associated with more favorable stock recommendations.

In this study, income smoothing is measured by the negative correlation between the change in accruals and the change in pre-managed earnings (e.g. Tucker and Zarowin 2006). A high negative correlation between changes in accruals and changes in pre-managed earnings indicates more income smoothing than does a low negative correlation. In contrast, the smoothness of a reported earnings series (i.e. the lack of earnings variability) is measured by the standard deviation of change in reported earnings (Barth, Elliott and Finn 1999).

In order to examine the utilization of smoothed earnings information by analysts when formulating their forecasts, we rely on the test of rationality of expectations (Maddala 1992). Rationality, as proposed by Muth (1961), refers to whether analysts utilize all known, relevant information in an unbiased and efficient manner. Hence a 'rational' forecast would be more accurate with respect to actual earnings than a forecast that is biased and inefficient. The rational expectations approach to testing the efficiency of forecasts of economic variables is well established (e.g. Brown and Maital 1981; Ito 1990). Studies that have tested for bias or efficiency (or both characteristics) of analysts' forecast include Mendenhall (1991), Abarbanell and Bernard (1992), Ali, Klein and Rosenfeld (1992) and Bradshaw, Richardson and Sloan (2001).

The results in this study show that the null hypothesis for efficiency of forecast with respect to income smoothing is not rejected, when the firm's reported earning show low variability. Earnings forecasts are, however, not efficient with respect to income smoothing when the reported earnings series is volatile. An increase in income smoothing in the presence of high reported earnings variability results in more negative forecast errors. The negative forecast error is due to a greater change in earnings forecasts, compared to the change in actual earnings, when there is an increase in income smoothing. These findings suggest that analysts' forecasts of earnings are more accurate when income smoothing by managers results in a stable reported

earnings series. Analysts are relatively more optimistic about firm's prospects when managers smooth earnings in high earnings variability situations.

Our study also provides evidence that in addition to using smoothed earnings information to generate earnings forecast, in certain situations, analysts also use the information to formulate stock recommendations. At high levels of reported earnings variability, an increase in income smoothing is associated with less favorable recommendations. At low levels of reported earnings variability, income smoothing by managers does not affect the analysts' recommendations.

Our results demonstrate that although analysts' forecasts are not efficient with respect to smoothed earnings information when reported earning series is volatile, analysts recommendations do reflect a lower assessment for firms that smooth earnings but fail to reduce the variability in reported earnings. An implication of our results is that the accuracy of earnings forecast (as measured by forecast error) is one aspect of the analysts' contribution to the efficient functioning of capital markets; the appropriateness of their recommendations is also important.

Our study contributes to the income smoothing and analysts' forecast literatures by demonstrating that information contained in smooth earnings affects analysts' forecasts of earnings and stock recommendations. In particular, we show that (i) income smoothing by managers, which leads to low earnings variability, results in more efficient earnings forecasts by analysts, and (ii) income smoothing by managers leads to less favorable stock recommendations, if the smoothing does not result in low reported earnings variability.

2 Background

2.1 Use of smoothed earnings information for earnings forecasts

Theoretical studies on income smoothing propose that managers smooth earnings in order to communicate information about the firm's future earnings prospects to investors (Demski 1998; Chaney and Lewis 1995; Sankar and Subramanyam 2001). Managers can utilize the discretion in GAAP to smooth earnings (Healy and Wahlen 1999; Schipper 1989). The smoothing action by managers should result in a pattern of smooth reported earnings in order for communication of prospects to occur (Demski 1998; Chaney and Lewis 1995).

There is empirical support for these ideas. Graham, Harvey and Rajgopal (2005) report that nearly all (97%) managers in their survey indicated that they prefer reported earnings to show a smooth pattern over time. Investors also attribute a higher value to firms that report smooth increasing earnings over time, and that a discontinuity in the reported earnings series results in a decrease in firm value (Barth et al. 1999). Rountree, Weston and Allayannis (2008) further find that an increase in the variability in cash flows (a component of earnings) decreases firm value. A recent study by Tucker and Zarowin (2006) provides a direct test of whether income smoothing using accruals provides investors with information about firm prospects. Their study demonstrates that managers' use of accruals to smooth earnings improves the predictability of past earnings for future earnings. Subramanyam (1996) also finds that discretionary accruals convey information about a firm's prospects based on his analysis of the relationship between discretionary accruals and stock returns.

Analysts' earnings forecasts are an essential input to an investor's assessment of the worth of a firm. Analysts' forecasts should therefore encapsulate all variables that have an effect on future earnings (Muth 1961). Gu and Chen (2004) find that analysts, on average, are able to isolate and

incorporate the persistent component of "non-recurring" items in order to provide more accurate earnings forecasts. The results in their study suggest that smoothed reported earnings would provide analysts with a more precise metric to predict future earnings. Consequently, if managers use income smoothing to communicate firm prospects, one would expect that analysts' forecast reflect the information about smoothed earnings.

Existing evidence on whether analysts fully incorporate relevant information in their forecasts (i.e. whether forecasts are rational) is inconclusive. Givoly (1985) finds that consensus forecasts of analysts are rational with respect to past earnings information. There is also support for the rationality of individual earnings per share forecast (e.g. Keane and Runkle 1998). Other studies (e.g. Medenhall 1991; Bradshaw, Richardson and Sloan 2001; De Bondt and Thaler 1990; Abarbanell and Bernard 1992), however, find that analysts' forecasts are biased and inefficient.

A recent study by Dichev and Tang (2009) provides further evidence of the inefficient use of information by analysts. Dichev and Tang find that past forecast errors are more 'persistent' for low volatility firms than for high volatility firms. In essence, Dichev and Tang tested a "weak" version of rationality (see Maddala 1992) because their tests include only the effect of previous forecast errors and its interaction with earnings variability on current forecast errors. This study extends the work of Dichev and Tang by testing a "strong" version of rationality (Maddala 1992), which requires that the forecast error should be uncorrelated with all the variables that are known to the analysts at the time of the forecast. We therefore directly test how income smoothing, the smoothness of reported earnings, and their investment affect forecast errors.

2.2 Use of smoothed earnings information for stock recommendations

The type of recommendation issued by analysts reflects the analysts' assessment of the firm's intrinsic value with respect to its current stock price. Buy recommendations, for instance, are issued when the analyst expects future growth in earnings, and that the firm's intrinsic value is above the firm's current stock price. The intrinsic value of the firm can be generated from several valuation models such as the discounted cash flow model, and the residual income model. The main input to these models is the forecast of future earnings.

A study by Bradshaw (2004) finds that long-term growth forecast is the most significant variable that explains variations in stock recommendations. Estimates of firm values obtained from sophisticated valuation models such as the residual income model are not significantly related to recommendations. Theoretical studies by Demski (1998) and Chaney and Lewis (1995) suggest that growth prospects can be revealed by firms through the smoothing of reported earnings. In a content analysis of analysts' research reports, Previts et al. (1994) find that analysts prefer firms that have smooth earnings. Consequently if analysts use the information contained in smooth earnings in their evaluation of the firm's future prospects, we expect that smooth earnings information to be significantly associated with the favorableness of the stock recommendations. Our study provides a test of the relationship between smooth earnings information and stock recommendations.

3 Research design

3.1 Income smoothing versus smoothness of reported earnings

Two aspects of the information contained in smoothed earnings are examined: income smoothing and the smoothness of reported earnings (Sunder 1997). Income smoothing is the use

of accruals to dampen fluctuations in earnings (Roden and Sadan 1981). In contrast, the smoothness of reported earnings is the lack of variability in the reported earnings series.

The smoothness of an earnings series or its variability (*EV*) is measured by the standard deviation of earnings change[1] over time. Barth et al. (1999) report that managers smooth earnings growth, and higher market valuation are associated with firms that show continuous earnings growth over time. Income smoothing (*IS*) is the negative correlation between the change in discretionary accruals and change in pre-managed earnings over a period of time (Tucker and Zarowin 2006; Myers, Myers and Skinner 2007; Leuz, Nanda and Wysocki 2003). A negative correlation signifies that an increase in discretionary accruals is associated with a decrease in pre-managed earnings. A high negative correlation is used to indicate more smoothing than a low negative correlation. A positive correlation implies that a change in accruals is in the same direction as the change in pre-managed earnings. In order to control for time and industry effects, Tucker and Zarowin (2006) use a reversed fractional ranking of the correlation to represent the extent of income smoothing by a firm. A negative correlation between accruals and pre-managed earnings is assigned a higher rank than a positive correlation. A fractional rank is obtained by dividing the assigned rank by the number of firms within the industry-year. In order to allow for comparisons with extant literature, in this study, we report regression results using both measures of smoothing, actual correlation (*IS1*), and the reversed ranked correlation (*IS*2)[2].

[1] The standard deviation of a non-stationary earnings series (e.g. a growing earnings series) will be high, but the standard deviation for its change in earnings will be low. We also performed the analysis using standard deviation on earnings levels instead of earnings change. The results are similar to those using standard deviation of earnings change.

[2] However, in order to conserve space, only the results for *IS1* for the slope analysis are reported.

The amount of discretionary (*DA*) and non-discretionary accruals (*NDA*) is estimated from equation 1. This estimation model for accruals is the cross-sectional version of Jones' (1991) model, which was developed by Kothari, Leone and Wasley (2005).

$$Acc = \delta_0 + \delta_1 \Delta Sales_t + \delta_2 PPE_t + \delta_3 ROA_t + \mu_t \quad (1)$$

where *Acc* is the total accruals (COMPUSTAT item *ni* less *Compustat* item *oancf*) deflated by beginning of the period total assets (COMPUSTAT item *at*); *ΔSales* is sales in period *t* minus the sales in period *t-1* (COMPUSTAT item *sales*) deflated by beginning of the period total assets; *PPE* is the gross level of plant property and equipment(COMPUSTAT item *ppe*), deflated by beginning of the period total assets; and *ROA* is the net income (COMPUSTAT item *ni*) divided by beginning of the period total assets.

Equation 1 is first estimated for all firms within the same two-digit SIC code in each year. The coefficients from the regression are used to calculate the amount of non-discretionary accruals (*NDA*) for each firm within the same two-digit SIC industry. The discretionary accruals (*DA*) are the residuals obtained by subtracting the *NDA* from actual accruals. The pre-managed earnings (*PME*) for each firm are then calculated by subtracting *DA* from net income. The change in pre-managed earnings and the change in discretionary accruals are then used to compute *IS*.

3.2 Tests of rationality of analysts' forecast

The rational expectations hypothesis proposed by Muth (1961) has been used to test whether analysts fully incorporate information relevant to the prediction of future earnings (e.g. Givoly 1985; Keane and Runkle 1991). The concept of rational expectations states that expectations should be generated by the same variables in the information set that affect the variables to be

forecasted. To test for rationality of a forecast, both the bias and efficiency of the forecast are evaluated. An earnings forecast is unbiased when its deviation from the realized earnings arises from random shocks. An efficient forecast is one in which information relevant for the prediction of the economic variable is fully utilized in its prediction (Muth 1961). An accurate earnings forecast therefore lacks bias and is efficient.

The linear regression equation for testing unbiasedness is given by equation 2 (Zarnowitz 1985; Keane and Runkle 1990, 1998).

$$A_{i,t} = \alpha_0 + \alpha_1 F_{i,t} + \varepsilon_{i,t} \tag{2}$$

where for each firm i, A_t is the actual earnings per share (EPS) for fiscal period t, F_t is the analysts' consensus forecast of earnings per share for fiscal period t, as reported by I/B/E/S one month after the earnings for the fiscal period t-1 is announced. A test of unbiasedness of the analysts' earnings forecast requires $\alpha_0 = 0$ and $\alpha_1 = 1$, which we test using the Wald statistic.

The test of efficiency investigates whether the forecast errors in period t is uncorrelated with the variables in the information set known to the analysts in period t-1. A common estimation method is to regress forecast errors in period t on variables in the information set at period t-1. The forecast error is the difference between actual earnings in period t and earnings forecast in a period t (equation 3). Givoly (1985), Abarbanell and Bernard (1992), Keane and Runkle (1998), and Dichev and Tang (2009) use this undeflated version of forecast error in their analysis. Other studies (e.g. Mendenhall 1991) use a deflated forecast error as dependent variable (with price as a deflator) in order to test the efficiency of earnings forecast. The use of a deflated forecast error as dependent variable tests the rationality of the predicted ratio of earnings and price (inverse of P/E ratio), instead of the rationality of earnings forecast. In this study we use the undeflated version of forecast errors.

The analyst forecast error, $FE_{i,t}$ for firm i is defined in equation 3:

$$FE_{i,t} = A_{i,t} - F_{i,t} \tag{3}$$

where $A_{i,t}$ is firm i's actual earnings for the forecast period t; and $F_{i,t}$ is firm i's median consensus earnings forecast for period t, available within one month of the most recent earnings announcement.

Equation 4 shows the estimation model used to test the rational expectations hypothesis for analysts' forecasts. Our primary focus is the coefficients on *IS*, *EV* and their interaction, (*IS* × *EV*)

$$FE_{i,t} = \beta_0 + \beta_1 IS_{i,t-1} + \beta_2 EV_{i,t-1} + \beta_3 (IS_{i,t-1} \times EV_{i,t-1}) + \beta_4 CE_{i,t-1} + \beta_5 Ret_{i,t-1} + \beta_6 PFE_{i,t-1} + \varepsilon_{i,t} \tag{4}$$

where, for firm i, $FE_{i,t}$ is the forecast error for fiscal year t as defined in equation 3; $IS_{i,t-1}$ is the degree of smoothing measured by the correlation (or reversed fractional ranking) of the change in yearly discretionary accruals and change in yearly pre-managed earnings from fiscal years t-1 to t-5; $EV_{i,t-1}$ is the standard deviation of change in yearly earnings from fiscal years t-1 to t-5; ($IS_{i,t-1} \times EV_{i,t-1}$) is the interaction between smoothing, $IS_{i,t-1}$ and $EV_{i,-1t}$; $CE_{i,t-1}$ is the percentage change in earnings from the previous fiscal year (t-2) to the most recent fiscal year (t-1); $Ret_{i,t-1}$ is the one-year holding stock returns of firm i up to the date of the forecast; and $PFE_{i,t-1}$ is the past forecast error for firm i relating to fiscal year t-1 earnings. Figure 1 illustrates how the variables in equation 4 relate to the earnings announcement dates and fiscal years.

The null hypothesis states that there is no relationship between the variables present in the information set available in period *t-1* and the forecast errors for period *t*. The coefficient for each of the dependent variables in equation 4 is therefore hypothesized to be zero.

Additional control variables (*CE, Ret, and PFE*) are included in equation 4. Prior-year change in earnings, *CE*, is included in equation 4 because previous studies (e.g. Fried and Givoly 1982;

Abarbanell and Bernard 1992; Debondt and Thaler 1985) have shown that analysts do not fully incorporate the information contained in past earnings in their forecasts. The inclusion of past returns, *Ret,* is motivated by studies (e.g. Beaver, Lambert and Morse 1980, 1987; Collins, Kothari and Rayburn 1987), which show that past stock returns reveal information about future earnings. Ali et al. (1991) show that past forecast errors are positively associated with current forecast errors. Past forecast errors, *PFE*, is therefore included in the equation 4.

Equation 4 also includes an interaction term ($IS \times EV$), which is a product of two continuous variables. Our approach differs from studies that use the product of a dummy variable and a continuous variable to examine interaction effects. In these studies (e.g. Elgers and Lo 1994; Ali et al. 1992) a dummy variable is first created from one of the continuous variables. The product between the dummy variable and the remaining continuous variable is the interaction term to be included in the regression equation. However, the use of a categorical (or dummy) variable in place of a continuous variable in a regression results in a loss of information, and creates measurement error from the dichotomization (Bollen and Barb 1981; Cohen 1983; Aiken and West 1991). Aiken and West (1991) suggest that the interaction of continuous variables can be used in regressions, but additional analysis of the interaction (which is discussed next) should be made. In this study, we examine the interaction between *IS* and *EV* in equation 4 as a product of two continuous variables.

The inclusion of a multiplicative term in equation 4 affects the interpretation of the coefficients on *IS* and *EV*. The regression coefficients for *IS* and *EV* now reflect conditional relationships, and additional analysis of the slope associated with *IS* and *EV* is required (also known as post-hoc probing in Aiken and West 1991). Equation 5a (5b) is obtained after differentiating *FE* with respect to *IS* (*EV*).

$$\frac{dFE}{dIS} = \beta_1 + \beta_3 EV \tag{5a}$$

$$\frac{dFE}{dEV} = \beta_2 + \beta_3 IS \tag{5b}$$

Equation 5a shows that the effect of smoothing on forecast errors depends on the level of earnings variability. Equation 5b shows the effect of *EV* on forecast errors depends on the level of *IS*.

A common way to analyze the slope for *IS* (*EV*) in equation 5a (5b) is to set *EV* (*IS*) to various levels of economically significant earnings variability (income smoothing) (Aiken and West 1991). For instance, an *EV* of zero indicates that the firm has no variability in past earnings. By substituting $EV = 0$ in equation 5a, β_1 shows the effect of smoothing on forecast errors when there is no variability in past earnings. Similarly, by substituting zero for *IS* in equation 5b, the effect of earnings variability on forecast errors is now β_2.

3.3 Use of smoothed earnings information in stock recommendations

In order to analyze whether analysts use smoothed earnings information in their formulation of stock recommendations, a two-stage least squares estimation of the following two equations is performed.

$$F_{i,t} = \varphi_0 + \varphi_1 IS_{i,t-1} + \varphi_2 EV_{i,t-1} + \varphi_3 (IS_{i,t-1} \times EV_{i,t-1}) + \varphi_4 CE_{i,t-1} + \varphi_5 Ret_{i,t-1} + \varphi_6 PFE_{i,t-1} + \varepsilon_{i,t} \tag{6a}$$

$$R_{i,t} = \lambda_0 + \lambda_1 IS_{i,t-1} + \lambda_2 EV_{i,t-1} + \lambda_3 (IS_{i,t-1} \times EV_{i,t-1}) + \lambda_4 F_{i,t} + \lambda_4 Prc_{i,t} + \lambda_4 (F_{i,t} \times Prc_{i,t}) + \mu_{i,t} \tag{6b}$$

where $R_{i,t}$ is the consensus stock recommendation in the month following the latest earnings announcement, $Prc_{i,t}$ is the share price of the firm prior to earnings forecast, and $(F_{i,t} \times Prc_{i,t})$ is

the interaction between price and earnings forecast for the firm, and all other variables are defined as in equation (4).

Bradshaw (2004) finds that stock recommendations are "more correlated with heuristic valuation models" than more sophisticated valuation models. Consequently, we do not incorporate the price of the stock via a valuation model in equation 6b. We include $F_{i,t}$, $Prc_{i,t}$ and ($F_{i,t}$ × $Prc_{i,t}$) directly into equation 6b in order to control for their effect on stock recommendations. $F_{i,t}$ is present in equation 6a as an independent variable, and as a dependent variable in equation 6b. Due the endogeneity of $F_{i,t}$, we use two-stage least squares to estimate equations 6a and 6b. (Johnston and Dinardo 1997).

4 Data and descriptive statistics

4.1 Data

The data for testing the hypotheses described in Section 3 are obtained from several sources. Data on the accounting variables for our analysis are obtained from the COMPUSTAT North America database. The median consensus one-year-ahead earnings forecasts and actual earnings, which are used to compute the forecast errors, are obtained from I/B/E/S. The stock returns and prices are obtained from the monthly security files available from CRSP.

4.2 Descriptive statistics

Table 1 provides a summary of the filters used to obtain the final sample. An initial sample of firms is drawn from the COMPUSTAT database. It comprises all firms that have data on variables needed to compute equations 1, 2 and 4 for the sample period 1988 to 2006. The year 1988 is the starting period for analysis because accruals are computed from cash flow statements,

which are available only from 1988. Our analysis focuses on non-financial and non-regulated firms. Consequently, firms with the two-digit SIC codes, 40-49 and 60-69, are removed from the sample. The consensus earnings forecasts are then obtained from I/B/E/S for the sample of firms obtained initially from COMPUSTAT. To be included in the final sample, we impose a minimum number of three earnings estimates used to compute the consensus earnings forecast. Stock returns and price data are then obtained for all usable firm observations. Observations for all variables reported in Table 1, except for the *IS* variable, that lie in the upper or lower 1% of their respective distributions are deleted in order to reduce the influence of extreme observations. The final pooled time-series and cross-sectional sample consists of 10,872 firm-year observations for the sample period 1988 to 2006.

Table 2 presents the descriptive statistics on the variables used in the estimation of equation 4. Consistent with previous studies (e.g. Lys and Sohn 1990; Givoly 1985), the mean *FE* is negative. The mean correlation between the change in accruals and the change in pre-managed earnings over a five-year period is positive. There are some firms within the sample whose changes in the accruals show an almost perfect negative (or positive) correlation with the pre-managed earnings. Variability in earnings change has a mean of $1.06, with a range of $0.08 to $8.00. The mean *PFE* is positive and close to zero, which contrasts with the negative mean for *FE*. The difference reflects the fact that the earnings forecast used to compute *PFE* is the forecast closest to the actual earnings announcement date, whereas the earnings forecast used to compute *FE* is the one that is immediately following the most recent earnings announcement (see Figure 1).

Table 2 panel B presents the Pearson (Spearman) correlation matrix for the variables used in the regression equation. As expected, the correlation between *IS1* and *IS2* is high and negative

because it reflects the reversed ranking used for *IS2*. The correlation between *IS1* and its interaction (*IS1* $\times$ *EV*) is also relatively high[3]. *IS1* is moderately correlated with *EV*. Similarly, *IS2* shows relatively high correlation with its interaction variable. *Ret* and *PFE* show moderate correlation with *FE*. The rest of the variables do not show a high correlation with each other.

5. Results and discussion

5.1 Unbiasedness of analysts' forecasts

Panel A in Table 3 shows the results from the estimation of equation 2. The intercept is negative, and the coefficient on the earnings forecast is positive. The null hypothesis for lack of bias requires that $\beta_0 = 0$ and $\beta_1 = 1$. The hypothesis that $\beta_0 = 0$ and $\beta_1 = 1$ is rejected at the 1% level of significance (Wald statistic =871.8). These results are consistent with the evidence of bias in analysts' forecasts reported by Abarbanell and Bernard (1992).

5.2 Efficiency of analysts' forecasts

5.2.1 Results using OLS estimation

Table 3 (panel B) shows that the coefficient on *IS1* is negative but is not significantly different from zero. The coefficient on *EV* is negative and significant at the 1% level. The interaction is positive and significant. The use of *IS2* in place of *IS1* affected the coefficient for the interaction term, which is now negative. This arises because of the definition of *IS2,* which is a reversed ranking of *IS1*. All three control variables (*CE*, *Ret* and *PFE*) have positive

[3] Aiken and West (1991) suggest that variables should be centered before including them in the interaction to reduce problems associated with multicollinearity (e.g. large standard errors, which leads to insignificance of the parameter estimates). There are studies (e.g. Echambadi and Hess 2007) that find that centering of variables does not resolve the multicollinearity problem in models with interaction between continuous variables. In our study, the high correlation between *IS* and its interaction term remains after centering. Centering the variables also make the interpretation of the results difficult. Consequently, we did not center the variables.

coefficients that are significantly different from zero at the 1% level. Our results are consistent with findings in extant literature (e.g. Ali et al. 1992), which show that analysts' forecasts do not fully incorporate information contained in *CE*, *Ret* and *PFE*.

The significance of the interaction variable (*IS* × *EV),* for both *IS1* and *IS2,* suggests that efficiency of analysts' forecast with respect to income smoothing depends on the variability of reported earnings. Because the interaction (*IS* × *EV*) is formed from two continuous variables (*IS* and *EV*), we conducted a "post-hoc probing" of the interaction as suggested in Aiken and West 1991, and discussed in section 3.2.

The analysis requires us to first rearrange equation 4 in order to show the impact of *EV* (*IS*) on the intercept, and the slope for *IS(EV)*.

$$FE_{i,t} = \beta_0 + \beta_1 IS_{i,t-1} + \beta_2 EV_{i,t-1} + \beta_3 (IS_{i,t-1} \times EV_{i,t-1}) + \beta_4 CE_{i,t-1} + \beta_5 Ret_{i,t-1} + \beta_6 PFE_{i,t-1} \varepsilon_{i,t} \quad (4)$$

$$FE_{i,t} = (\beta_0 + \beta_2 EV_{i,t-1}) + (\beta_1 + \beta_3 EV_{i,t-1}) IS_{i,t-1} + \beta_4 CE_{i,t-1} + \beta_5 Ret_{i,t-1} + \beta_6 PFE_{i,t-1} + \varepsilon_{i,t} \quad (7a)$$

$$FE_{i,t} = (\beta_0 + \beta_1 IS_{i,t-1}) + (\beta_2 + \beta_3 IS_{i,t-1}) EV_{i,t-1} + \beta_4 CE_{i,t-1} + \beta_5 Ret_{i,t-1} + \beta_6 PFE_{i,t-1} + \varepsilon_{i,t} \quad (7b)$$

Equation 7a shows that the intercept ($\beta_0+\beta_2 EV$), and slope for *IS* ($\beta_1+\beta_3 EV$), depends on the values of *EV*. Similarly, equation 7b shows that the intercept ($\beta_0+\beta_1 IS$), and slope for *EV* ($\beta_2+\beta_3 IS$), depends on the values of *IS*.

We provide the results of the slope analysis for equations 7a and 7b using *IS1* as the smoothing variable. For the sake of parsimony, we do not provide the results with *IS2*[4] as the smoothing variable. The use of *IS2* instead of *IS1* did not significantly alter our conclusions. Panel A in Table 4 provides the intercepts and slopes for *IS1* computed at each level of *EV*, where the levels are values taken at different points of the distribution of *EV*. The table shows that the intercept is negative regardless of the level of *EV*, although the magnitude declines when

[4] The results are available from the authors.

earnings variability declines. Consistent with the findings in previous studies (e.g. Ali et al. 1992), our results demonstrate that analysts' forecasts demonstrate a 'levels' bias, that is, earnings forecasts are, on average, higher than realized earnings.

Panel A in Table 4 also shows that the slope for *IS1* is negative when earnings variability is at or below the median, and is positive when earnings variability is above the median. The slopes for *IS1* are not significantly different from zero when reported earnings are not volatile. However, at higher levels of reported earnings variability, the slopes are significant at the 5% level. At high earnings variability, a greater amount of smoothing (i.e. a negative change in *IS1,* because smoothing is measured by the negative correlation between discretionary accruals and pre-managed earnings) is associated with a negative forecast error. For instance, at the 75th percentile of the *EV* distribution, a decrease in one unit of *IS2* (i.e. more smoothing) is associated with a negative \$0.008 change in forecast error. At the 90th percentile of the *EV* distribution, a decrease in one unit of *IS1* (i.e. more smoothing) is associated with a negative \$0.024 change in forecast error.

The null hypothesis that analysts fully incorporate the effects of income smoothing in their forecasts is not rejected at levels of earnings variability below the 75th percentile. These results demonstrate that analysts' forecasts are efficient with respect to information relating to income smoothing when income smoothing results in low earnings variability. At high levels of earnings variability, analyst forecasts are not efficient with respect to information contained in income smoothing.

Panel B of Table 4 presents the slope for *EV* at various degrees of income smoothing. In our study, income smoothing is measured by the negative correlation between changes in accruals and changes in pre-managed earnings. Our analysis therefore focuses on the negative values of

income smoothing (below the 25% percentile of the *IS1* distribution) in panel B. The slopes for *EV* are significant at the 1% level for all levels of income smoothing. The negative slopes for *EV* shows that when there is income smoothing, an increase in earnings variability results in negative forecast errors[5]. The null hypothesis that analysts' forecasts fully incorporate the information with respect to earnings variability is rejected when firms practice income smoothing. When firms do not show income smoothing (in accordance to our definition of income smoothing), we do not reject the null hypothesis that analysts forecast is efficient with respect to information on earnings variability.

5.2.2 Zellner's seemingly unrelated regression

We further examine the effect of smoothing information on earnings forecast and actual earnings by using Zellner (1962) 'seemingly unrelated' regression (SURE) to estimate the paired regressions in equation 8.

$$A_{i,t} = \beta_0 + \beta_1 IS_{i,t-1} + \beta_2 EV_{i,t-1} + \beta_3 (IS_{i,t-1} \times EV_{i,t-1}) + \beta_4 CE_{i,t-1} + \beta_5 Ret_{i,t-1} + \beta_6 PFE_{i,t-1} + \varepsilon_{i,t} \quad \text{(8a)}$$

$$F_{i,t} = \alpha_0 + \alpha_1 IS_{i,t-1} + \alpha_2 EV_{i,t-1} + \alpha_3 (IS_{i,t-1} \times EV_{i,t-1}) + \alpha_4 CE_{i,t-1} + \alpha_5 Ret_{i,t-1} + \beta_6 PFE_{i,t-1} + \mu_{i,t} \quad \text{(8b)}$$

where $A_{i,t}$ and $F_{i,t}$ are the actual and forecast earnings for firm *i* at time period *t*. The description of the dependent variables in equation 8 is the same as that in equation 4. An advantage of this technique is that the effect of smoothed earnings information on earnings and forecasts is separately computed. The SURE approach is appropriate for the estimation of earnings and forecast regression because general economic or industry factors that have an influence on a firm's future earnings, are likely to simultaneously affect its earnings forecast. Consequently, the

[5] As will be discussed in Section 4.2.2, the results from the ISURE regression show that the negative change in forecast errors is due to the fact that the change in analysts' forecasts is more than the change in actual earnings when there is an increase in earnings variability.

$\varepsilon_{i,t}$ and $\mu_{i,t}$ in equations 8a and 8b will be correlated. The SURE approach takes into account the cross-correlation of the error terms by estimating the two equations jointly, which results in a gain in efficiency in parameter estimation. This SURE method of analysis has been used to evaluate the efficiency of expectations of macroeconomic time series (e.g. Friedman 1980; Pesando 1975; see also Maddala 1992 for details).

The null hypothesis for efficiency of forecast requires that the $\beta_j = \alpha_j$, where $j = 0,\ldots 6$. We adopt interactive SURE (ISURE) in our estimation of equations 8a and 8b. The ISURE method is similar to the SURE method except that in ISURE, the parameters in equations 8a and 8b are re-estimated in each step by using a new error covariance matrix, until no further change in the parameter estimates is obtained. Consequently the ISURE method is an improvement over the SURE method.

Panel A of Table 5 shows the results of the ISURE estimation of equations 8a and 8b. In the earnings regression, the coefficient for *IS1* is negative and significant, but is insignificant in the forecast regression. The coefficients for *EV* in both regressions are positive and significant. The interaction between the *EV* and *IS1* is negative and is significant in both regressions. The Wald test for the equality of the respective coefficients for *IS1*, *EV* and (*IS1* × *EV)* in the earnings and forecast regressions is conducted. We reject the null hypothesis of equality of coefficients for *EV* and (*IS1* × *EV).* These results are consistent with those reported in Section 4.2.1, which show that *EV* and (*IS1* × *EV*) are significantly related to forecast errors. Similar but slightly weaker results are obtained when *IS2* is used in the regression[6].

Panel B presents a comparison of the slopes for *IS1* for the earnings and forecast regressions respectively, at various levels of *EV*. The negative slope for *IS1* indicates that more smoothing

[6] Note that the sign of the interaction term is reversed because of the definition of *IS2*, which is a reversed ranking of *IS1*).

(a decrease in *IS1*) is associated with higher earnings and higher earnings forecast. For *EV* above the median level of *EV*, the slope for *IS1* in the forecast regression is higher than that of the earnings regression. At *EV* below the median, the slope for *IS1* in the forecast regression is lower than that for the earnings regression.

Our results from the simultaneous equation estimation therefore provide further insight into the positive slope for *IS1* with respect to forecast errors reported in Table 4 (panel A). In our analysis in section 5.2.1, we show that when there is high earnings variability, an increase in smoothing (represented by a negative change in *IS1*) is associated with a negative forecast error. The negative forecast error occurs because there is a greater change in consensus analysts' forecasts than actual earnings, given the increase in smoothing. Analysts appear to be more optimistic about earnings prospects when managers smooth earnings in high earnings variability situations.

Panel C of Table 5 shows that the slopes for *EV* in the forecast regression are larger than those in the earnings regression at all levels of smoothing. In Section 5.2.1, we report that an increase in earnings variability results in more negative forecast errors. Our results from the ISURE estimation show that negative forecast errors arise because the change in analysts' forecasts is greater than the change in earnings for each unit increase in earnings variability.

Our results therefore demonstrate that analysts' consensus forecasts efficiently incorporate information in income smoothing, but only in the presence of low earnings variability. In other words, communication by managers about earnings prospects through income smoothing appears to be assimilated by analysts in their consensus forecast of one-year-ahead earnings, when income smoothing occurs in conjunction with smoothed earnings series. In contrast, when there is a high level of earnings variability, an increase in smoothing by a firm generates more

optimistic forecasts from analysts compared to the firm's actual earnings. Consensus earnings forecasts are therefore not efficient with respect to income smoothing by managers when the resulting reported earnings series is volatile.

5.3 Results on the use of smooth earnings information in recommendations.

Table 6 presents the results of the two-stage least squares regression for equations 6a and 6b. In the estimated equation 6b, the coefficient for *IS1* is insignificant, but the coefficient for (*IS1* × *EV*) is negative and significant at the 5% level. The results for *IS2* are similar to those for *IS1*. A further analysis of the slope of *IS1* (Table 6 panel B), evaluated at various levels of *EV*, shows that at high levels of earnings variability (75th percentile and above), an increase in income smoothing (i.e. a more negative *IS1*) is associated with less favorable recommendations. However, at low levels of variability, income smoothing by managers does not significantly affect analysts' recommendations. Panel C of Table 6 shows that a decrease in earnings variability is associated with more favorable recommendations, regardless of the level of income smoothing. At higher levels of income smoothing, a decrease in earnings variability is associated with a greater change in the favorableness of the recommendations.

Panel A in Table 6 also shows that the coefficients on *F* and *Prc* are both negative and significant at the 1% level. The interaction between the two variables is positive and significant, which suggests that the effect of earnings forecast on recommendations depends on the price of the stock at the time of recommendation. Using the post-hoc probing technique suggested by Aiken and West (1991), we analyzed the effect of earnings forecast on recommendations at various levels of share prices prior to the earnings forecast. The untabulated results show that when prices are low, an increase in earnings forecast is associated with more favorable

recommendations. In contrast when prices are high, an increase in earnings forecast is associated with less favorable recommendations. An analysis of the effect of prices on recommendations at various levels of earnings forecast, shows that at low (high) earnings forecast levels, an increase in share price is associated with more (less) favorable recommendations.

6 Concluding remarks

This study examines whether analysts fully incorporate information contained in smoothed earnings when making predictions about future earnings, and whether smoothed earnings information is associated with more favorable recommendations. Income smoothing is the use of accruals to reduce the fluctuations around a time series of reported earnings. Income smoothing is measured by the correlation between the change in discretionary accruals and change in pre-managed earnings. The smoothness of the earnings series is measured by the variability in change in earnings. For managers to successfully communicate information about firm prospects, the use of accruals to smooth earnings must generate a smooth reported earnings series. This study investigates the effect of income smoothing, earnings variability and their interaction on forecast errors and stock recommendations.

Our study demonstrates that the interaction between income smoothing and earnings variability affects both analysts' forecasts and recommendations. We find that analysts' forecasts are efficient with respect to information about smoothed earnings when income smoothing occurs in the presence of low earnings variability series. However, when past earnings variability is high, an increase in income smoothing leads to negative forecast errors. An increase in income smoothing results in a greater increase in earnings forecast compared to actual earnings. Analysts appear to be more optimistic about a firm's future earnings when income smoothing occurs in

high earnings variability situations. Our results also extend findings of Dichev and Tang (2009) by showing that analysts do not efficiently incorporate the information on earnings variability when firms exhibit income smoothing. However, when there is no income smoothing (as defined in our study), earnings forecasts efficiently reflect the information contained in earnings variability.

Our results on analysts' recommendations show that analysts do use smoothed earnings information in formulating recommendations in certain situations, in addition to using the information to generate earnings forecasts. While we did not find that greater income smoothing is associated with more favorable recommendations, we find that when reported earnings variability is high, an increase in income smoothing is associated with less favorable recommendations. Analysts therefore do not view income smoothing as a signal of healthy firm prospects if the reported earnings show a high variability. These results suggest that although analysts may not be efficient in their forecast of earnings with respect to smooth earnings information, their evaluation of firm prospects for their stock recommendation is consistent with the information contained in smooth earnings.

Our study has the following limitations. First, we assume that the smoothing of earnings by managers can be captured by the negative correlation between pre-managed earnings and discretionary accruals. Second, our study relies on the Kothari et al.'s (2005) model to estimate discretionary accruals. Therefore, the results reported in this study are conditional on the appropriateness of this model in capturing the non-discretionary component of reported accruals. Last, we assume that forecasts and recommendations that are available within one month of the most recent earnings announcement will incorporate the smoothed earnings information.

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Table 1

Description of filters applied to data from COMPUSTAT, CRSP and I/B/E/S in order to obtain final sample

Nature of filter	**Number of firm-year observations remaining**
All COMPUSTAT data from financial year 1988 to 2006	118,993
Removed firm-year observations that have insufficient information to compute discretionary accruals.	110,532
Removed firm-year observations that have fewer than 10 firms within the industry-year for computing non-discretionary accruals	109,624
Removed firm-year observations that do not have continuous 5-year data to compute *IS* and *EV*	52,501
Removed firm-year observations that do not have available information on consensus forecasts (at least three forecasts must be available for each consensus estimate) in I/B/E/S in the period following the earnings announcement	15,460
Removed firm-year observations that do not have available information on returns and prices from CRSP (25993)	15,299
Removed firm-year observations that are in industry SIC codes 40-49 and 60-69.	12,304
Removed firm-year observations that do not have available information for equations 4 and 6.	12,255
Removed firm-year observations that are beyond the 1% and 99% percentile of the distribution for each of the variables described in equation 4.	10,872
Final sample	10,872

Table 2

Descriptive statistics

Panel A: Simple Statistics

Variable	Mean	Standard Deviation	Median	Minimum	Maximum
FE	-0.129	0.474	-0.020	-3.250	1.490
IS1	0.122	0.538	0.154	-0.999	1.000
IS2	0.527	0.288	0.528	0.005	1.000
EV	1.064	1.051	0.722	0.082	7.990
CE	0.232	1.756	0.099	-10.378	14.750
Ret	0.195	0.427	0.170	-0.970	1.771
PFE	0.003	0.087	0.010	-0.690	0.440

Table 2

Panel B: Pearson (Spearman) correlation of independent variables in equation 4

Variable	*FE*	*IS1*	*IS2*	*EV*	*CE*	*Ret*	*PFE*	*IS1 × EV*	*IS2 × EV*
FE		-0.003	-0.009	-0.038	0.056	0.178	0.143	-0.004	-0.042
IS1	0.005		-0.947	0.199	0.017	-0.002	0.006	0.697	-0.409
IS2	-0.018	-0.950		-0.212	-0.023	-0.007	-0.008	-0.674	0.428
EV	0.011	0.198	-0.199		0.040	0.006	0.010	0.520	0.521
CE	0.089	0.025	-0.034	0.026		0.157	0.078	0.040	-0.018
Ret	0.219	-0.008	-0.001	0.004	0.216		0.138	0.001	-0.005
PFE	0.200	0.003	-0.005	0.061	0.130	0.180		0.019	0.000
IS1 × EV	0.011	0.924	-0.879	0.293	0.034	-0.004	0.010		-0.329
IS2 × EV	0.000	-0.547	0.576	0.510	-0.010	-0.001	0.056	-0.420	

The descriptive statistics are obtained for 10,872 firm year observations over the sample period 1992 to 2006 for firms. Spearman correlation coefficients are below the diagonal in the table in Panel B, and Pearson correlation coefficients are above the diagonal in the table.

Definition of variables

FE is actual earnings for year *t* minus the median consensus analysts earnings forecast for year *t*, available within one month of the earnings announcement for year *t*-1.

IS1 is a measure of smoothing. It is calculated as the correlation of change in discretionary accruals and change in pre-managed earnings over the five most recent fiscal years. A negative correlation indicates smoothing of earnings by managers.

IS2 is a second measure for smoothing of earnings. It is the reversed fractional ranking (ranked within industry and year) of *IS1*.

EV is the standard deviation of the yearly change in reported earnings for the five most fiscal years.

CE is the percentage change in reported earnings from the previous fiscal year to the most recent fiscal year.

PFE is the past forecast error for the most recent earnings announcement. It is computed as the difference between actual earnings for year *t-1* and the latest consensus forecast available prior to the announcement of year *t-1* earnings.

Ret is the one-year holding stock returns up to the date of the forecast.

IS1×EV is the interaction between smoothing, *IS1* and *EV*.

IS2×EV is the interaction between smoothing, *IS2* and *EV*.

Table 3
Ordinary Least Square Regression Results

Panel A: Regression results for equation 2

$A_{i,t} = \alpha_0 + \alpha_1 F_{i,t} + \varepsilon_{i,t}$

	α_0	α_1	R^2
Estimate	-0.094	0.968	0.845
t-statistic	-14.75	243.22	

Joint test of $\alpha_0 = 0$ and $\alpha_1 = 1$ is rejected at the 1% level (Wald statistic is 871.79)

Panel B: Ordinary least squares regression results for the following equation

$FE_{i,t} = \beta_0 + \beta_1 IS_{i,t-1} + \beta_2 EV_{i,t-1} + \beta_3 \left(IS_{i,t-1} \times EV_{i,t-1} \right) + \beta_4 CE_{i,t-1} + \beta_5 Ret_{i,t-1} + \beta_6 PFE_{i,t-1} + \varepsilon_{i,t}$

estimated using, respectively, *IS1* (actual correlation between change in discretionary accruals and change in pre-managed earnings) and *IS2* (reversed fractional ranking of *IS1* ranked within industry and firm year) as proxies for *IS*.

Regression	Variable	Intercept	*IS1*	*EV*	*IS1 × EV*	*IS2*	*IS2 × EV*	*CE*	*Ret*	*PFE*
1	Estimate	-0.143	-0.014	-0.025	0.017			0.006	0.175	0.653
	t-statistic	-20.619	-1.141	-4.784	2.060			2.395	16.510	12.667
	Two-tailed *p*-value	0.000								
	One-tailed *p*-value		0.127	0.000	0.020			0.008	0.000	0.000
2	Estimate	-0.141		-0.012		-0.001	-0.031	0.006	0.175	0.655
	t-statistic	-11.340		-2.021		-0.040	-1.872	2.336	16.490	12.701
	Two-tailed *p*-value	0.000								
	One-tailed *p*-value			0.022		0.484	0.031	0.010	0.000	0.000

§ *IS2* is a reversed fractional ranking of *IS1*. Consequently, the sign of the coefficient for *IS2* × *EV* is expected to be opposite to that for *IS1* × *EV*.

Table 4
Results on analysis of the interaction between *IS* and *EV*

Panel A: Slope for income smoothing, *IS1*, at different levels of earnings variability, *EV*.

Quantile	Estimate	Intercept	Slope for *IS1* at these values of *EV*#	t-statistics	
100% Max	7.990	-0.339	0.119	2.10	*
99%	5.466	-0.277	0.077	2.11	*
95%	3.102	-0.219	0.038	2.04	*
90%	2.266	-0.199	0.024	1.85	*
75% Q3	1.319	-0.175	0.008	0.94	
50% Median	0.722	-0.161	-0.002	-0.19	
25% Q1	0.406	-0.153	-0.007	-0.70	
10%	0.243	-0.149	-0.010	-0.90	
5%	0.180	-0.147	-0.011	-0.97	
1%	0.113	-0.146	-0.012	-1.04	
0% Min	0.082	-0.145	-0.012	-1.07	

A positive slope indicates that a decrease in *IS1* (i.e. more smoothing, because smoothing is measured by the negative correlation between discretionary accruals and pre-managed earnings) is associated with a negative change in forecast error. A negative slope indicates that a decrease in *IS1* is associated with a positive change in forecast errors.

Panel B: Slope for earnings variability, *EV*, at different levels of income smoothing, *IS1*.

Quantile	Estimate	Intercept	Slope for *EV* at these values of *IS1*§	t-statistics
100% Max	1.000	-0.157	-0.008	-1.18
99%	0.977	-0.156	-0.008	-1.26
95%	0.910	-0.155	-0.009	-1.51
90%	0.837	-0.154	-0.011	-1.83*
75% Q3	0.584	-0.151	-0.015	-3.15**
50% Median	0.154	-0.145	-0.022	-4.80**
25% Q1	-0.308	-0.139	-0.030	-4.36**
10%	-0.657	-0.134	-0.035	-3.88**
5%	-0.791	-0.132	-0.038	-3.73**
1%	-0.933	-0.130	-0.040	-3.59**
0% Min	-0.999	-0.129	-0.041	-3.53**

§ A positive slope indicates that an increase in earnings variability is associated with an increase in forecast error. A negative slope indicates that an increase in earnings variability is associated with a negative change in forecast error.

*indicates significance at the 5% level.

** indicates significance at the 1% level.

Equation 4 shows the relationship between forecast errors and the variables assumed to be available in the information set of the analysts at the time of the forecast.

By rearranging the equation, we get the intercept, $\beta_0+\beta_2 EV$ and slope $\beta_1+\beta_3 EV$, which are both dependent on the values of *EV*.

$$FE_{i,t} = \beta_0 + \beta_1 IS_{i,t-1} + \beta_2 EV_{i,t-1} + \beta_3 IS_{i,t-1} \times EV_{i,t-1} + \beta_4 CE_{i,t-1} + \beta_5 Ret_{i,t-1} + \beta_6 PFE_{i,t-1} \varepsilon_{i,t} \quad (4)$$

$$FE_{i,t} = (\beta_0 + \beta_2 EV_{i,t-1}) + (\beta_1 + \beta_3 EV_{i,t-1}) IS_{i,t-1} + \beta_4 CE_{i,t-1} + \beta_5 Ret_{i,t-1} + \beta_6 PFE_{i,t-1} + \varepsilon_{i,t} \quad (7a)$$

$$FE_{i,t} = (\beta_0 + \beta_1 IS_{i,t-1}) + (\beta_2 + \beta_3 IS_{i,t-1}) EV_{i,t-1} + \beta_4 CE_{i,t-1} + \beta_5 Ret_{i,t-1} + \beta_6 PFE_{i,t-1} + \varepsilon_{i,t} \quad (7b)$$

The intercepts and slopes are computed at different points of the distribution of *EV* (*IS1*) in order to examine the effect *IS1* (*EV*) at different levels of *EV*(*IS1*).

Table 5
Seemingly unrelated regression results

Panel A: Seemingly unrelated regression results for the following equations

$$A_{i,t} = \beta_0 + \beta_1 IS_{i,t-1} + \beta_2 EV_{i,t-1} + \beta_3 \left(IS_{i,t-1} \times EV_{i,t-1} \right) + \beta_4 CE_{i,t-1} + \beta_5 Ret_{i,t-1} + \beta_6 PFE_{i,t-1} + \varepsilon_{i,t} \quad (8a)$$

$$F_{i,t} = \alpha_0 + \alpha_1 IS_{i,t-1} + \alpha_2 EV_{i,t-1} + \alpha_3 \left(IS_{i,t-1} \times EV_{i,t-1} \right) + \alpha_4 CE_{i,t-1} + \alpha_5 Ret_{i,t-1} + \alpha_6 PFE_{i,t-1} + \mu_{i,t} \quad (8b)$$

estimated using, respectively, *IS1* (actual correlation between accruals and pre-managed earnings) and *IS2*(reversed fractional ranking of IS1 by industry and firm year) as proxies for *IS*.

Dependent variable	Parameter	Intercept	*IS1*	*EV*	*IS1 × EV*	*IS2*	*IS2 × EV*	*CE*	*Ret*	*PFE*
Regression 1										
A	Estimate	0.876	-0.045	0.073	-0.026			0.062	0.124	2.402
	t-statistic	49.946	-1.475	5.649	-1.267			9.506	4.634	18.430
	Two-tailed *p*-value	0.000								
	One-tailed *p*-value		0.007	0.000	0.103			0.000	0.000	0.000
F	Estimate	1.019	-0.031	0.098	-0.042			0.056	-0.051	1.749
	t-statistic	60.670	-1.069	7.874	-2.174			8.937	-1.980	14.013
	Two-tailed *p*-value	0.000								
	One-tailed *p*-value		0.143	0.000	0.015			0.000	0.024	0.000
Regression 2										
A	Estimate	0.902		0.005		-0.101	0.228	0.063	0.125	2.398
	t-statistic	28.642		0.318		-1.933	5.420	9.724	4.677	18.420
	Two-tailed *p*-value	0.000								
	One-tailed *p*-value			0.375		0.027	0.000	0.000	0.000	0.000
F	Estimate	1.043		0.017		-0.100	0.259	0.057	-0.050	1.744
	t-statistic	34.612		1.168		-2.003	6.436	9.193	-1.933	13.991
	Two-tailed *p*-value	0.000								
	One-tailed *p*-value			0.122		0.023	0.000	0.000	0.027	0.000

§ *IS2* is a reversed fractional ranking of *IS1*. Consequently, the sign of the coefficient for *IS2* is expected to be opposite to that for *IS1*.

Test results for the following hypotheses

	Regression 1		Regression 2	
Test	Wald Statistic	Prob> *ChiSq*	Wald Statistic	Prob> *ChiSq*
β_1-α_1=0	1.30	0.25	0.002	0.968
β_2-α_2=0	22.88	0.00	4.084	0.043
β_3-α_3=0	4.25	0.04	3.503	0.061

Panel B: Slope analysis for *IS1* at different levels of earnings variability, *EV*

		Earnings regression				Forecast regression			
Quantile	**Value**	**Intercept**	**Slope for *IS1* at these values of *EV***	**t-statistics**		**Intercept**	**Slope for *IS1* at these values of *EV***	**t-statistics**	
100% Max	7.990	1.461	-0.250	-1.756	*	1.800	-0.369	-2.759	**
99%	5.466	1.276	-0.185	-2.011	*	1.553	-0.262	-3.032	**
95%	3.102	1.103	-0.124	-2.661	**	1.322	-0.162	-3.696	**
90%	2.266	1.042	-0.103	-3.159	**	1.240	-0.127	-4.149	**
75% Q3	1.319	0.972	-0.078	-3.572	**	1.148	-0.087	-4.205	**
50% Median	0.722	0.929	-0.063	-2.825	**	1.089	-0.061	-2.930	**
25% Q1	0.406	0.906	-0.055	-2.197	*	1.059	-0.048	-2.048	*
10%	0.243	0.894	-0.051	-1.886	*	1.043	-0.041	-1.630	
5%	0.180	0.889	-0.049	-1.774	*	1.036	-0.039	-1.482	
1%	0.113	0.884	-0.047	-1.658	*	1.030	-0.036	-1.329	
0% Min	0.082	0.882	-0.047	-1.606		1.027	-0.034	-1.262	

Panel C: Slope analysis for *EV* at different levels of earnings variability, *IS1*

Quantile	**Value**	**Intercept**	**Slope for *EV* at these values of *IS1***	**t-statistics**	**Intercept**	**Slope for *EV* at these values of *IS1***	**t-statistics**
100% Max	1.000	0.831	0.048	2.766**	0.988	0.056	3.444**
99%	0.977	0.832	0.048	2.861**	0.989	0.057	3.580**
95%	0.910	0.835	0.050	3.151**	0.991	0.059	3.997**
90%	0.837	0.839	0.052	3.500**	0.993	0.062	4.500**
75% Q3	0.584	0.850	0.058	4.881**	1.001	0.073	6.531**
50% Median	0.154	0.869	0.069	5.986**	1.014	0.091	8.403**
25% Q1	-0.308	0.890	0.081	4.724**	1.028	0.111	6.873**
10%	-0.657	0.905	0.090	3.903**	1.039	0.126	5.793**
5%	-0.791	0.911	0.094	3.666**	1.043	0.131	5.478**
1%	-0.933	0.917	0.097	3.453**	1.048	0.137	5.193**
0% Min	-0.999	0.920	0.099	3.365**	1.050	0.140	5.075**

*indicates significance at the 5% level.

** indicates significance at the 1% level.

Table 6

Results on use of smoothed earnings information in stock recommendations

Panel A: Two-stage least squares results for the following equations

$$F_{i,t} = \beta_0 + \beta_1 IS_{i,t-1} + \beta_2 EV_{i,t-1} + \beta_3 IS_{i,t-1} \times EV_{i,t-1} + \beta_4 CE_{i,t-1} + \beta_5 Ret_{i,t-1} + \beta_6 PFE_{i,t-1} + \varepsilon_{i,t} \quad (6a)$$

$$R_{i,t} = \alpha_0 + \alpha_1 IS_{i,t-1} + \alpha_2 EV_{i,t-1} + \alpha_3 IS_{i,t-1} \times EV_{i,t-1} + \alpha_4 F_{i,t} + \alpha_5 Prc_{i,t} + \alpha_6 (F_{i,t} \times Prc_{i,t}) + \mu_{i,t} \quad (6b)$$

where $R_{i,t}$ is the median consensus stock recommendation. In I/B/E/S, a strong buy recommendation is coded '1', a sell recommendation is coded '5'. Consequently, a higher number for R indicates a less favorable recommendation.

Dependent variable	***Parameter***	***Intercept***	***IS1***	***EV***	***IS1 × EV***	***IS2§***	***IS2 × EV***	***CE***	***Ret***	***PFE***	***F***	***Prc***	***F × Prc***
Regression 1													
	Estimate	1.019	-0.031	0.098	-0.042			0.056	-0.051	1.749			
F	t-statistic	60.670	-1.069	7.874	-2.174			8.937	-1.980	14.013			
	Two-tailed p-value	0.000	0.285	0.000	0.030			0.000	0.048	0.000			
	One-tailed p-value		0.142	0.000	0.015			0.000	0.024	0.000			
R	Estimate	2.727	-0.003	0.057	-0.026						-0.578	-0.015	0.013
	t-statistic	35.862	-0.153	6.809	-2.034						-5.932	-9.187	6.596
	Two-tailed p-value	0.000	0.879	0.000	0.042						0.000	0.000	0.000
	One-tailed p-value		0.439	0.000	0.021						0.000	0.000	0.000

Dependent variable	***Parameter***	***Intercept***	***IS1***	***EV***	***IS1 × EV***	***IS2§***	***IS2 × EV***	***CE***	***Ret***	***PFE***	***F***	***Prc***	***F × Prc***
Regression 2													
F	Estimate	1.043		0.259		-0.100	0.017	0.057	-0.050	1.744			
	t-statistic	34.612		6.436		-2.003	1.168	9.193	-1.933	13.991			
	Two-tailed p-value	0.000		0.000		0.045	0.243	0.000	0.053	0.000			
	One-tailed p-value			0.000		0.023	0.121	0.000	0.027	0.000			
R	Estimate	2.727		0.033		-0.010	0.058				-0.575	-0.015	0.013
	t-statistic	36.731		3.430		-0.289	2.167				-5.868	-9.128	6.518
	Two-tailed p-value	0.000		0.001		0.773	0.030				0.000	0.000	0.000
	One-tailed p-value			0.000		0.386	0.015				0.000	0.000	0.000

§ *IS2* is a reversed fractional ranking of *IS1*. Consequently, the sign of the coefficient for *IS2* is expected to be opposite to that for *IS1*.

Panel B: Slope analysis for *IS1* at different levels of earnings variability, *EV,* for the consensus recommendation regression in the regression (1) in panel A

Quantile	Estimate	Intercept	Slope for smoothing at these values of *EV*	t-statistics
100% Max	7.990	3.186	-0.212	-2.35**
99%	5.466	3.041	-0.146	-2.50**
95%	3.102	2.905	-0.084	-2.83**
90%	2.266	2.857	-0.062	-2.98**
75% Q3	1.319	2.803	-0.038	-2.61**
50% Median	0.722	2.768	-0.022	-1.50
25% Q1	0.406	2.750	-0.014	-0.84
10%	0.243	2.741	-0.009	-0.53
5%	0.180	2.737	-0.008	-0.43
1%	0.113	2.733	-0.006	-0.32
0% Min	0.082	2.732	-0.005	-0.27

Panel C: Slope analysis for *EV* at different levels of smoothing, *IS1,* for the consensus recommendation regression in the regression (1) in panel A

Quantile	Estimate	Intercept	Slope for *EV* at these values of *IS1*	t-statistics
100% Max	1.000	2.724	0.031	2.85**
99%	0.977	2.724	0.032	2.96**
95%	0.910	2.724	0.034	3.32**
90%	0.837	2.724	0.036	3.74**
75% Q3	0.584	2.725	0.042	5.45**
50% Median	0.154	2.727	0.053	7.06**
25% Q1	-0.308	2.728	0.066	5.92**
10%	-0.657	2.729	0.075	5.05**
5%	-0.791	2.729	0.078	4.79**
1%	-0.933	2.730	0.082	4.55**
0% Min	-0.999	2.730	0.084	4.45**

*indicates significance at the 5% level.
** indicates significance at the 1% level.

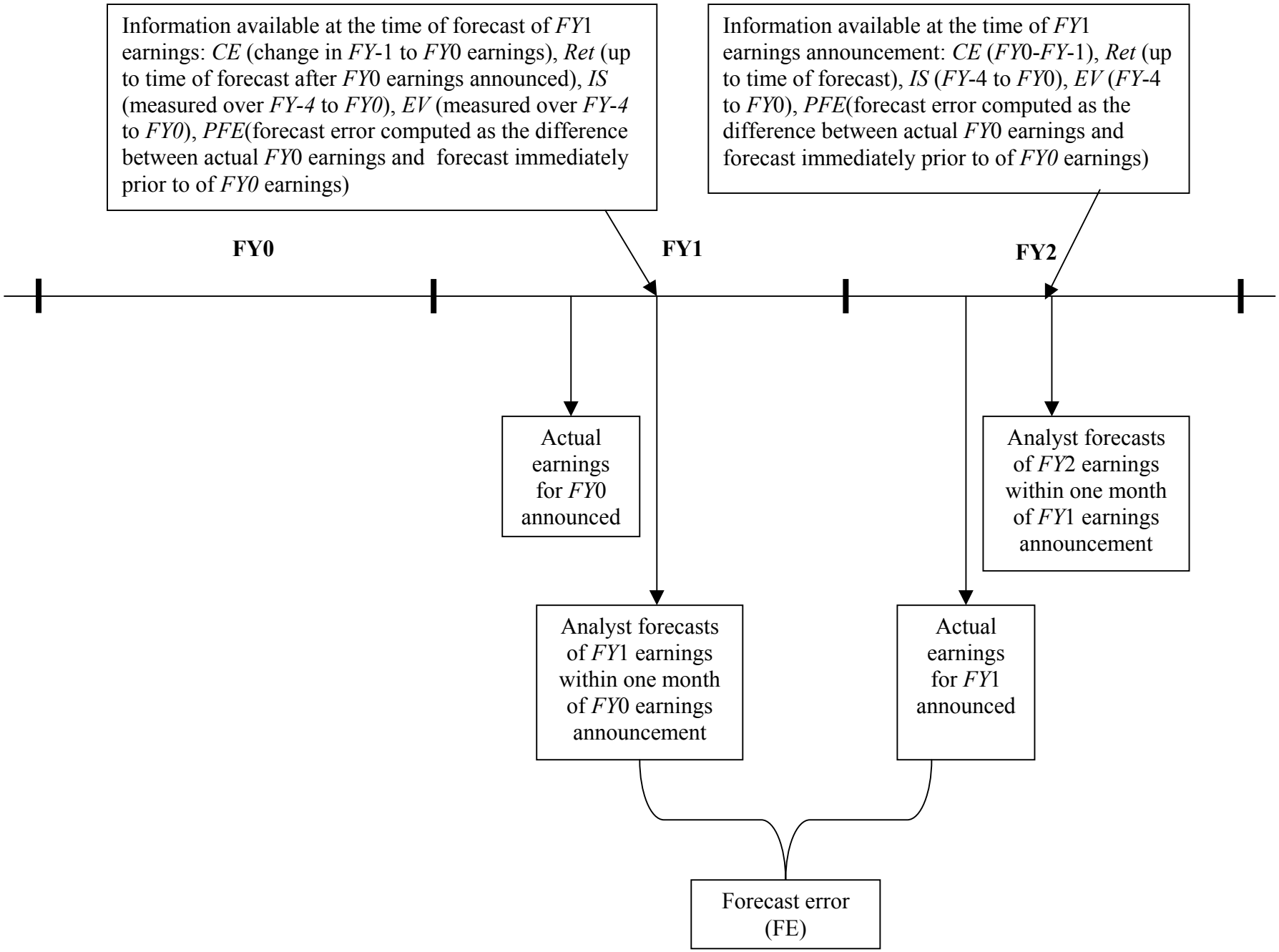

Figure 1: Timeline showing how variables for equation 4, 8a and 8b are obtained